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Assembled product manufacturers often introduce line extensions that share components with existing products, or among themselves, resulting in *cost interactions* among products because of shared costs, and *revenue interactions* because of cannibalization. We present a cross-functional approach to evaluating multiple line extensions that simultaneously considers revenue implications of component sharing at the *product level* and cost implications at the *component level*. We develop a source-of-volume model and a measurement procedure to decompose the life-cycle sales volume from a line extension into sales from cannibalization, competitive draw, and demand expansion. We develop an activity-based costing procedure for estimating the life-cycle costs of line extensions that share components. We develop an optimization model that uses these revenue and cost estimates to identify a subset of line extensions that maximizes incremental profits. We implement our approach at a quartz wristwatch manufacturer. Results suggest that our approach would have improved profits for the firm by over 5%, while actually launching *fewer* line extensions. We also find that the drivers of cannibalization are counterintuitive. In simulation studies, our approach outperforms three managerial heuristics. We demonstrate that this approach is most valuable when cannibalization dominates competitive draw as a source of volume, and discuss its relative merits under low and high parts-sharing.
(*Product Variety; Component Variety; Profit Maximization; Cost Interactions; Revenue Interactions*)

1. Introduction

The optimal level of variety a firm should offer has long been recognized as a trade-off between satisfying heterogeneous market needs and achieving manufacturing economies of scale (Lancaster 1996, 1990; MacDuffie et al. 1996; Kahn 1998; Krishnan et al. 1998, Sawhney 1998). In recent years, manufacturers of assembled products have responded to the variety challenge by sharing components among products.

Component sharing creates *cost interactions* among products due to shared costs. Researchers in operations have examined how component sharing can reduce the costs of variety (Fisher et al. 1999, Gupta and Krishnan 1998, Ramdas 1995). However, sharing components can also increase cannibalization, creating *revenue interactions* between "look-alike" products. Researchers in marketing have focused on the selection of line extensions to maximize revenues and minimize cannibalization (Green and Krieger 1985, Schmalensee and Thisse 1986). More recently, some models for product variety have included costs (Yano and Dobson 1998). However, we are unaware of any product-line evaluation models that account for both the cost interactions and the revenue interactions caused by component sharing. We attempt to bridge this gap by developing a cross-functional approach

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that integrates the revenue and cost implications of component sharing in evaluating line extensions for assembled products.

For assembled products, the process of selecting line extensions involves the following steps: (1) definition of product platforms or families that may share components, (2) a process to generate a master set of all potential line extensions, (3) a model to evaluate the revenues and costs from the introduction of a set of line extensions, including the impact of revenue and cost interactions, (4) a method to identify the subset of line extensions that maximizes incremental profits, and (5) a measurement method to operationalize the approach.

We focus on steps 3, 4, and 5 above, for platform-based assembled products such as wristwatches, cameras, laser printers, and VCRs. For such products, there is a fundamental difference between the way firms *create* variety, and the way consumers *evaluate* variety. From the operations perspective, each new component results in incremental development and support costs that can be traced to individual components. From the marketing perspective, consumers evaluate the product as a whole (Srinivasan et al. 1997). Component sharing affects perceived differentiation and incremental revenues from line extensions, but this effect is not directly traceable to individual components. We believe that this dichotomy explains the gap in the literature between research that examines the *cost impact* of component sharing and research that focuses on the *market impact* of product variety.

Our approach has several unique contributions. First, we recognize that the revenue impact of line extensions is best evaluated at the *product level*, while their cost impact is best evaluated at the *component level*. We develop a source-of-volume model to decompose the sales volume for a set of line extensions into sales from cannibalization, competitive draw, and demand expansion. We develop an activity-based costing procedure to estimate the life-cycle costs of a set of line extensions that share components based on the newness and complexity of their designs. We develop a mixed-integer programming model that uses these estimates, which incorporate both revenue and cost interactions, to identify the subset of line extensions that maximizes incremental profits.

We also develop measurement methods for the source-of-volume model and the activity-based costing model, to implement our approach. As a by-product, we are able to offer insights on the *type* of variety to include in the master set of line extensions.

We implement our approach at a firm in the quartz wristwatch industry. We demonstrate its validity by its ability to predict life-cycle sales of line extensions, and by showing that this approach could have improved the firm's life-cycle profits from line extensions by over 5%, while actually launching *fewer* line extensions. We benchmark our approach against three heuristic approaches, and find it provides the greatest benefit over these approaches when cannibalization dominates competitive draw as a source of volume. If the line extensions in the master set exhibit high parts-sharing, our model is most beneficial when selecting a small subset of them to introduce. In contrast, if the line extensions being considered exhibit low parts-sharing, our model is most beneficial when selecting a large subset of them to introduce.

In the next section, we review the relevant literature. In §§3 and 4, we describe the methodology for estimating the incremental revenue and incremental cost of a set of line extensions. In §5, we develop the optimization model and describe the solution procedure. In §6, we describe an empirical application, and use stimulation to examine the relative merits of our cross-functional optimization model over heuristic approaches, under different levels of cannibalization and component sharing. The last section summarizes and concludes.

2. Relevant Literature on Product Line Evaluation

Revenue Approaches to Product Line Design

Marketing models for product line design generate optimal product profiles that maximize revenues or market share, using conjoint analysis or perceptual mapping to estimate preferences (Green and Krieger 1985, Schmalensee and Thisse 1986, Nair et al. 1995, McBride and Zufryden 1988). Dobson and Kalish

(1988, 1993) include a fixed cost for each product in a conjoint product line design model. More recently, researchers have modified conjoint product line design models to include cost interactions among products (see Dobson and Yano 1998 for a review). Raman and Chhajed (1995) model attribute-level fixed costs that may be shared across products, with the attributes that consumers evaluate treated as the attributes that determine manufacturing costs. In practice, however, consumers evaluate *product attributes*, while manufacturing costs are driven by *components*. Dobson and Yano (1995) model cost interactions due to shared or product-specific engineering and design resources, within a conjoint framework. None of these models address the impact of component sharing on consumer choice, and few have been implemented.

We depart from the literature by developing and implementing a model that considers the impact of shared components on both the incremental costs and the incremental revenues from line extensions. We also provide a demand estimation procedure to consider *multiple line extensions* simultaneously. In this situation, the pairwise demand interactions among products are complex. To simplify demand estimation, we take advantage of the fact that a line extension is likely to draw sales from a relatively small set of close substitutes among existing (firm and competitor) products, which we describe as its *baseline set*. Unlike conventional new product forecasting models (cf. Urban 1993), we estimate sales from primary demand expansion, in addition to cannibalization and competitive draw.

In conjoint product line design, cannibalization is estimated indirectly by first estimating consumer utility for a new product via part-worth utility functions over a few product attributes, and then using these to estimate cannibalization. This indirect approach has limitations when some product dimensions, e.g., aesthetics, cannot be adequately described by a few objective attributes (Srinivasan et al. 1997). We overcome this problem by directly measuring pairwise cannibalization between prototypes, without relying on a decompositional approach to estimate consumer utility. This procedure is simpler than the conjoint measurement procedure, and is more valid for products with a high aesthetic dimension. Dahan and Srinivasan (1998) use prototypes in conjoint concept selection, but they do not incorporate costs.

Cost Approaches to Variety Management

Researchers in operations have examined the role of product modularity and component sharing in creating high variety from a small set of component building blocks (Ulrich 1995, Krishnan et al. 1998, Ulrich and Ellison 1999). Prescriptive models trade off the cost of designing and purchasing additional components against the mismatch cost associated with using existing components with excess capability (Rutenberg 1969, Ramdas 1995, Gupta and Krishnan 1998, Fisher et al. 1999). While operations researchers recognize the cost implications of component sharing, the impact of component sharing on consumer preferences over the product line is poorly understood. We contend that revenue analysis is the missing link in the cost-benefit analysis of component-sharing strategies. Ulrich (1995) calls for models that integrate marketing science with cost models to evaluate optimal variety strategies. Our approach is a step in this direction.

Measuring New Product Costs

Traditional cost accounting systems assume that products consume overheads in proportion to volume. Activity-Based Costing (ABC) systems (Cooper and Kaplan 1988) trace support costs more accurately to products via cost drivers that measure support resource consumption. Early ABC systems focused on support costs for existing products. More recent extensions estimate the manufacturing costs associated with new product designs, primarily to guide target costing (Foster and Gupta 1990, Hertenstein and Platt 1998).

We develop an activity-based technique to estimate the development costs of multiple line extensions that share components, to guide line extension decisions. Development costs for multiple line extensions need to be jointly estimated for the *set* of line extensions, as the cost for each line extension depends on how much it shares components with existing products

and other line extensions. Also, unlike existing products, resource consumption rates for line extensions are unknown. We model cost interactions among multiple line extensions, and propose a procedure to forecast costs for line extensions, for which historical cost data are unavailable.

3. Estimating Incremental Revenues from Multiple Line Extensions

To estimate the incremental revenues from a set of line extensions over their life cycle, we need to estimate their life-cycle sales volume from different *sources* of volume. *Demand expansion* is sales volume from new consumers, who would not have purchased an existing (firm or competitor) product; *competitive draw* is sales volume from consumers who would have otherwise purchased a competitor product; *cannibalization* is sales volume from consumers who would have otherwise purchased one of the firm's existing products. Unlike cannibalization, demand expansion and competitive draw are incremental sales to the firm.

Conventional simulated test market procedures (Silk and Urban 1978, Urban et al. 1984, Cohen et al. 1997) generally estimate sources of volume for a single line extension. However, high-variety firms often introduce multiple line extensions simultaneously. This requires us to estimate the potential demand interactions between *multiple* line extensions and the existing product line, an intractable task because of the combinatorial nature of all possible pairwise demand interactions. To simplify this task, we take advantage of the fact that a line extension is likely to draw sales from a relatively small set of close substitutes among existing (firm and competitor) products. Therefore, cannibalization and competitive draw for a line extension can be limited to a restricted set of models that constitute an independent *competitive submarket* within the overall market (Kannan et al. 1991, Urban et al. 1984). We define the *baseline set* for each line extension as the set of firm and competitor models that are its closest substitutes, determined a priori by consumer categorization, observed cross-price elasticities, forced substitution, or managerial judgment.

Once the baseline sets have been defined, cannibalization and draw are estimated via a "forced augmentation" procedure. Each line extension is introduced into its baseline set, and the observed switching from the baseline models to the line extension is measured. We assume the following:

Assumption 1. *A line extension can draw sales only from its a priori defined baseline set, or through primary demand expansion.*

Assumption 2. *There is no pairwise cannibalization between two or more line extensions that have partly overlapping baseline sets. This is often likely to be a relatively small second-order effect.*

Assumption 3. *Line extensions have a finite life cycle, consistent with high-variety firms. Such firms often engage in planned obsolescence. We assume an equal life-cycle length for all line extensions.*

Assumption 4. *The preference share that a line extension draws from a baseline model can be scaled to estimate sales volume, based on estimated life-cycle volume of the baseline model.*

Assumption 5. *Line extensions achieve full awareness and distribution in the first year of launch. This assumption is typical of simulated test market models* (*cf. Urban* 1993).

Assumptions 1 and 2 make the estimation of cannibalization and competitive draw tractable by restricting demand interactions to the baseline sets, and ignoring interactions among line extensions. Assumptions 3 and 4 enable us to convert preference shares into life-cycle volume estimates. Assumption 5 allows us to calibrate consumer response without test marketing.

Estimating Primary Demand Expansion

Let $\mathbf{B}_k$ denote the baseline set for line extension k, $\mathbf{B}$ the universe of baseline sets, and $\mathbf{N}$ the set of line extensions. The augmented universe of products after the introduction of the line extensions is $\{\mathbf{B}, \mathbf{N}\}$. Define:

$$P(Buy \mid \mathbf{B}) = \text{Probability of category purchase, given the baseline universe } \mathbf{B}$$

$P(Buy \mid \mathbf{B}, \mathbf{N})$ = Probability of category purchase, given the augmented universe $\{\mathbf{B}, \mathbf{N}\}$

$P(k \mid \mathbf{N})$ = Preference share for line extension k, given consideration set $\mathbf{N}$.

Let Q_j denote life-cycle sales volume for existing product j in $\mathbf{B}$. We estimate total demand expansion due to the line extensions as:

$$Q^E = \left[\frac{P[(Buy \mid \mathbf{B}, \mathbf{N}) - P(Buy \mid \mathbf{B})}{P(Buy \mid \mathbf{B})}\right] \sum_{j \in \mathbf{B}} Q_j. \quad (1)$$

We partition Q^B into the expansion attributable to each line extension k over its life cycle based on the preference share for the line extension among the set of $\mathbf{N}$ line extensions, so that:

$$Q_k^E = P(k \mid \mathbf{N}) \cdot Q^E. \quad (2)$$

Estimating Cannibalization and Competitive Draw

We use a "forced augmentation" procedure, in which the share of preference for each line extension is measured before and after its introduction into its baseline set. The share of preference lost by each existing model to the line extension, scaled by its sales volume, is summed over the firm's own models in the baseline set to estimate cannibalization, and over the competitor models in the baseline set to estimate competitive draw. Let δ_{jk} denote the share points lost by model j in the baseline set to line extension k, Q_k^C the life-cycle sales volume for line extension k because of cannibalization, $Q_{k,j}^C$ the portion of Q_k^C attributable to baseline model j, and Q_k^D the life-cycle sales volume for line extension k because of competitive draw. Then,

$$Q_k^C = \sum_{\substack{j \in \mathbf{B}_k \\ j \in Firm's\ Models}} Q_{k,j}^C = \sum_{\substack{j \in \mathbf{B}_k \\ j \in Firm's\ Models}} \delta_{jk} Q_j$$

$$= \sum_{\substack{j \in \mathbf{B}_k \\ j \in Firm's\ Models}} \frac{P(j \mid \mathbf{B}_k) - P(j \mid \{\mathbf{B}_k, k\})}{P(j \mid \mathbf{B}_k)} Q_j, \quad (3)$$

and

$$Q_k^D = \sum_{\substack{j \in \mathbf{B}_k \\ j \in Competitor's\ Models}} \delta_{jk} Q_j$$

$$= \sum_{\substack{j \in \mathbf{B}_k \\ j \in Competitor's\ Models}} \frac{P(j \mid \mathbf{B}_k) - P(j \mid \{\mathbf{B}_k, k\})}{P(j \mid \mathbf{B}_k)} Q_j. \quad (4)$$

Where:

$P(j \mid \mathbf{B}_k)$ = Preference share for model j in $\mathbf{B}_k$ before introducing line extension k.

$P(j \mid \{\mathbf{B}_k, k\})$ = Reduced preference share for j after $\mathbf{B}_k$ is augmented with line extension k.

Let p_k^N and p_j^B denote the unit prices of line extension k and baseline model j respectively, and ΔR_k the incremental revenue from introducing line extension k.

$$\Delta R_k = p_k^N (Q_k^D + Q_k^E) + \sum_{\substack{j \in \mathbf{B}_k \\ j \in firm's\ models}} (p_k^N - p_j^B) Q_{k,j}^C \quad (5)$$

Summing ΔR_k over all line extensions introduced gives the incremental revenue from any subset of line extensions. Also, the total sales volume for line extension k is:

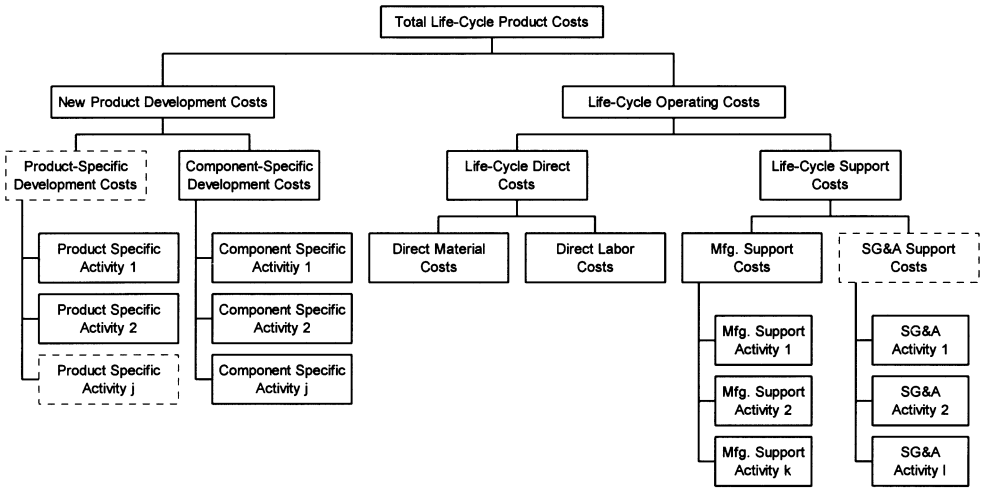
$$Q_k^T = Q_k^C + Q_k^D + Q_k^E \quad (6)$$

4. Estimating Incremental Life-Cycle Costs of Multiple Line Extensions

We view life-cycle product costs as the costs of all activities associated with a line extension (product) over its life cycle, comprised of development costs and life-cycle operating costs. Development costs are one-time costs associated with bringing the new product to market. Life-cycle operating costs are the direct costs and ongoing support costs incurred over the product's life cycle. Development costs are either product-specific, pertaining to development activities that are undertaken once for each new product, or component-specific, pertaining to activities that are undertaken once for each new component, regardless of how many products it is used in. For example, in auto manufacturing, concept creation is a product-specific activity, whereas sparkplug design is a component-specific activity. Figure 1 contains our life-cycle cost classification.

We estimate costs at the product and component level, where components may be shared across products. Let k denote a specific product, c a specific

Figure 1 Activity-Based Classification of Life-Cycle Product Costs.



component, and s a specific version of component c. With this notation, each c, s identifies a unique component version. For example, for a wristwatch, if $c = 1$ denotes the dial then $1, 2$ would represent dial version 2. We assume that each product uses one unit of each component.

Measuring Development Costs

We define *development intensity* for each product (each component version) as the degree of difficulty in performing all of its product-specific (component-specific) activities relative to other products (other versions of the same component). We model development intensity as the product of two underlying design attributes, complexity and newness. This approach captures the key drivers of development cost, and yet is relatively is easy to implement.

We categorize each new product into one of L different levels of increasing design complexity. To do this we require design engineers to first categorize all existing products, and then judgmentally benchmark the new products against the existing products. Each complexity level $l \in \{1, 2, \ldots, L\}$ is represented by a numerical value $r_l^C \in (0, 1]$, with $r_L^C = 1$ for the highest design complexity level. The numerical differences in r_l^C capture the relative differences in complexity between different design complexity levels. This categorization task is simpler for engineers than estimation of absolute design costs. We perform a similar complexity categorization for each component version by comparing it with other versions of the same component. For example, a new wristwatch case that is shaped and has several parts would likely be rated as more complex than an existing one-piece round case.

Similarly, all new products and component versions are categorized into L different levels of increasing design newness. Each newness level $l \in \{1, 2, \ldots, L\}$ is represented by a numerical value $r_l^N \in [0, 1]$, with $r_L^N = 1$ for a brand new design and $r_1^N = 0$ for an existing design. Again, this categorization task is simpler for engineers than estimation of absolute design costs. Let

$$\lambda_l^{D,k} = 1, \text{ if new product } k \text{ is assigned design complexity level } l, \text{ and 0 otherwise}$$

$$\lambda_l^{N,k} = 1, \text{ if new product } k \text{ is assigned design newness level } l, \text{ and 0 otherwise}$$

$$\lambda^k = \text{development intensity of new product } k$$

Then, $\lambda^k = \sum_{l,m \in L} \lambda_l^{D,k} \lambda_m^{N,k} r_l^C r_m^N$. Similarly, we calculate λ^{cs}, the development intensity of new component version c, s.

Next, as in a standard activity-based costing implementation, we use historical data to estimate the *unit resource costs* U_i for each machine or labor resource i. We estimate the *resource consumption levels* (in hours) of each resource i, for each product-specific or component-specific activity j, for the highest intensity product and highest intensity version of each

component c,[1] as R_{ij} and R^c_{ij}, respectively. For simplicity, we assume that all product-specific activities (component-specific activities) for a specific product (component version) have the same development intensity level.

The product-specific development cost for line extension k is estimated by determining its intensity level λ^k, determining the cost of its highest intensity counterpart via the activity-based approach, and scaling down by λ^k.

$$d_k = \lambda^k \sum_{\substack{j \in \text{product-specific} \\ \text{activities}}} \sum_i U_i R_{ij}. \tag{7}$$

Similarly, the component-specific development cost for new version s of component c is:

$$d_{c,s} = \lambda^{cs} \sum_{\substack{j \in \text{component-specific} \\ \text{activities}}} \sum_i U_i R^c_{ij}. \tag{8}$$

This procedure explicitly considers cost interactions due to component sharing. For instance, a line extension that shares components with existing products will be allocated zero development costs for the shared components, regardless of their development complexity. Further, in the optimization model, the cost to develop a component is counted only once regardless of how many line extensions it is used in, through the use of an indicator variable.

Measuring Lifecycle Operating Costs

Direct material costs $m_{c,s}$ for version s of component c are estimated based on prior experience with similar components. Direct labor costs for newly designed components typically decline with accumulated volume according to an experience curve, which measures the percentage decrease in labor costs with a doubling of cumulative production volume. Learning effects penalize newly designed components, especially if they are very complex or very new, and are used only in a few low-volume models. We approximate the experience curve as a two-piece linear function, so that direct labor costs for version s of component c drop from an initial higher level $l^1_{c,s}$ to a lower level $l^2_{c,s}$ when the cumulative production volume for the component exceeds the critical production level $E_{c,s}$. We estimate direct labor costs at the product level, l_k, based on costs for similar existing products.

Support costs can be estimated at the product level by classifying new product into different levels of "support intensity"[2] and then using standard ABC.

5. Optimizing Incremental Profitability from a Set of Line Extensions

We develop an optimization model that uses our incremental revenue and incremental cost estimates to select the subset of line extensions that maximizes total incremental profits. Let

X_k = product introduction indicator (1 if new model k in **N** is introduced, 0 otherwise);

$Y_{c,s}$ = component introduction indicator (1 if version s of component c is introduced, 0 else);

$W_{c,s}$ = critical production volume indicator (1 if cumulative production volume for version s of component c exceeds its critical production volume, 0 otherwise);

$V^1_{c,s}$ = production volume of version s of component c at the higher direct labor cost level; and

$V^2_{c,s}$ = production volume of version s of component c at the lower direct labor cost level.

Revenue Parameters

Estimation of all revenue parameters and cost parameters is discussed in §§3 and 4. As before,

$Q^C_{k,j}$ = sales for line extension k from cannibalization of baseline model j;

Q^T_k = total life-cycle sales for line extension k (Equation (6), §3); and

ΔR_k = incremental revenue from introducing line extension k (Equation (5), §3).

[1] Estimating resource usage at many intensity levels is possible in theory, but time consuming.

[2] Note that the *development intensity* for a product may be different from its *support intensity*.

Cost Parameters

Let

c_j = unit cost of baseline model j;

d_k = product-specific development cost for line extension k (Equation (7));

$d_{c,s}$ = component-specific development cost for version s of component c (Equation (8));

f_k = total life-cycle support cost for line extension k;

$E_{c,s}$ = critical production volume for version s of component c;

l_k = direct labor cost per unit for product k;

$l^1_{c,s}$ = direct labor cost per unit for version s of component c, at higher cost level;

$l^2_{c,s}$ = direct labor cost per unit for version s of component c, at lower cost level;

$m_{c,s}$ = unit direct material cost for version s of component c;

$\mathbf{S}_{c,s}$ = set of all new products that contain version s of component c; and

M = an arbitrarily large number.

Cross-Functional Model Formulation

$$\text{Maximize: } \sum_{k\in N} X_k \left\{ \Delta R_k + \sum_{\substack{j\in \mathbf{B}_k \\ j\in firm's\ models}} c_j Q^C_{k,j} - l_k Q^T_k \right\} - \sum_{k\in N} X_k (d_k + f_k) - \sum_{c,s} Y_{c,s} d_{c,s} - \sum_{c,s} \{ (m_{c,s} + l^1_{c,s}) V^1_{c,s} + (m_{c,s} + l^2_{c,s}) V^2_{c,s} \}. \quad (9)$$

Subject to:

$$Y_{c,s} \geq X_k \quad \forall k \in \mathbf{S}_{c,s}, \quad \forall c, s, \quad (10)$$

$$V^1_{c,s} + V^2_{c,s} = \sum_{k\in \mathbf{S}_{c,s}} X_k Q^T_k \quad \forall c, s, \quad (11)$$

$$E_{c,s} W_{c,s} \leq V^1_{c,s} \leq E_{c,s} \quad \forall c, s, \quad (12)$$

$$V^2_{c,s} \leq M W_{c,s} \quad \forall c, s, \quad (13)$$

$$V^1_{c,s}, V^2_{c,s} \geq 0 \quad \forall c, s, \quad (14)$$

$$X_k, Y_{c,s}, W_{c,s} \in \{0, 1\} \quad \forall k, c, s. \quad (15)$$

The problem as formulated above is a linear mixed-integer program. Equation (10) imposes the definition of the variables $Y_{c,s}$. Equations (11) through (14) impose the definitions of the volume-related variables $V^1_{c,s}$ and $V^2_{c,s}$, and Equation (15) imposes integrality restrictions. The objective function includes the incremental revenue from each set of line extensions, the product-specific and component-specific development costs, direct manufacturing costs for products and individual components, and support costs at the product level. Experience effects in labor costs are approximated by a two-piece piecewise linear labor cost function.

For fairly large problems, this problem was solved using the GAMS optimization software.[3] For larger problems, we developed a Lagrangean relaxation procedure (Fisher 1985) in combination with a Lagrangean heuristic to obtain a good feasible solution (see Appendix).

6. Empirical Application

We implemented our approach at Titan Industries Limited, an international manufacturer of analog quartz wristwatches, based in India.[4] The watch industry is an excellent setting for implementation, because watch manufacturers offer a wide variety of models in varying styles and price points. Titan offers over 1,000 wristwatches. It refreshes 10%–15% of its product line, and evaluates hundreds of line extensions each year. Effective variety management is key to profitability. Visible *appearance parts* (case, dial, hands, and strap) offer styling cues. Less visible *movement parts* (internal mechanical and electrical components) determine functional characteristics.

Titan sponsored a pilot implementation of our framework for a subset of 13 potential line-extension prototypes at the high end of their 1996 product line.

[3] Developed by the GAMS Development Corporation.

[4] For the sake of brevity, we refer to analog quartz wristwatches simply as "watches."

Management identified a baseline set of 4–6 close substitutes for each prototype. The baseline set universe consisted of 23 Titan models and 12 competitor models.[5] The relative proportion of Titan versus competitor models included in each baseline set was based on Titan's market share in the price range.

Consumer Measurement

A professional market research firm calibrated our source of volume model. A representative sample of 302 respondents who had indicated an interest in buying a new watch in the appropriate price range was recruited in two geographic locations, via random sampling. Respondents were invited into a simulated store setting. They were presented with different consideration sets of watches, and asked to allocate points among watches in each set.

1. Respondents were presented with the universe of 35 baseline models, with brands and prices revealed, and asked to indicate if they would buy any one of these models.

2. The baseline set universe was augmented with the 13 prototypes. Respondents were asked to indicate whether they would buy one of the models from the augmented universe. The fraction of respondents who indicated they would buy from the augmented, but not the baseline, universe measures demand expansion because of all prototypes.

3. Respondents were asked to allocate points among the 13 prototypes to measure the relative strength of preference for them. Using this measure, total demand expansion because of all prototypes was decomposed into demand expansion for each prototype.

4. Five baseline sets were chosen for evaluation by each respondent.[6] Respondents were presented with each baseline set, and asked to allocate points among the baseline models. The baseline set was then augmented with the relevant prototype, and respondents were asked to reallocate points among the augmented set. The fraction of points lost by each baseline model was used to estimate cannibalization and competitive draw.

5. Respondents were also asked to evaluate the perceived pairwise similarity between the prototypes and each of the baseline models in their corresponding baseline sets.

Through this procedure, we estimated sales from primary demand expansion, cannibalization, and draw for each prototype. Management provided sales estimates for the baseline models for the estimated four–year life cycle. The experiment could also help determine how much customers might pay for variety by offering different versions of the same new product at different prices.

Cost Measurement

In collaboration with managers in Titan's accounting and engineering departments, we defined the development-related activities, identified the manpower and machine resources used in the development process, classified each prototype into appropriate complexity and newness levels, and estimated its product and component-specific development costs. It was not possible to implement an activity-based costing system for support costs. Therefore, we relied on the overhead allocation system used at Titan to estimate unit support cost for the baseline and prototype models, and multiplied unit support costs by life-cycle sales volumes to determine life-cycle support costs. Cooper and Kaplan (1988) suggest that using standard costing for support costs typically results in underestimation of the costs of new, low-volume products. Therefore, support costs are likely to be higher than our estimates suggest. The costs, sales prices, and sales volume estimates for the prototypes are summarized in Table 1. Note that the

[5] Due to overlap in baseline sets, the number of unique models in the baseline set universe (35) was less than the total number of models used to construct the baseline sets for specific prototypes (50).

[6] Each respondent first selected five most preferred models from {**B, N**}. If a favorite model was a prototype, it was included for evaluation by the respondent. If the favorite model belonged to $\mathbf{B_k}$, the prototype k associated with $\mathbf{B_k}$ was included. Because multiple favorite models could be chosen from the same baseline set, we could end up with less than five prototypes. Each respondent was then assigned randomly selected prototypes from the remaining prototypes, to make up a total of five. This procedure assures that respondents evaluate their most preferred prototypes, while also ensuring some data on the least preferred prototypes.

Table 1 Life-Cycle Sales Volumes and Costs for Line Extensions (in Rupees)

Line Extension	Life-Cycle Sales Volume (units)*	Total Life-Cycle Support Cost** (Rs.)	Product Specific Devt. Cost*** (Rs.)	Case Specific Devt. Cost (Rs.)	Dial Specific Devt. Cost (Rs.)	Module Specific Devt. Cost (Rs.)	Strap Specific Devt. Cost (Rs.)
1	11,076	2,938,770	6,000	42,000	750	–	240,000
2	17,265	5,505,305	6,000	42,000	3,750	–	150,000
3	12,081	3,561,986	6,000	42,000	3,750	–	240,000
4	11,422	3,704,986	76,000	277,200	3,750	–	150,000
5	29,219	9,514,600	76,000	277,200	3,750	–	150,000
6	59,719	19,287,590	76,000	138,600	2,500	–	150,000
7	19,484	5,578,325	76,000	70,000	20,000	–	–
8	10,237	4,117,321	76,000	560,000	20,000	–	27,000
9	12,923	4,758,285	76,000	630,000	17,500	–	27,000
10	22,268	8,300,939	76,000	700,000	6,000	–	27,000
11	13,035	5,298,271	58,000	210,000	6,750	–	270,000
12	15,499	6,282,707	58,000	700,000	6,000	–	270,000
13	7,292	1,900,979	6,000	42,000	6,000	–	150,000

* Based on consumer measurement procedure.
** Based on Titan's standard costing system and classification of support intensity of prototype.
*** These costs are based on the activity-based procedure described for estimating development costs.

design costs are very low relative to the support costs, reflecting that design is a labor-intensive activity, and skilled labor is very cheap in India. Design costs could be higher by an order of magnitude for a comparable U.S. manufacturer.

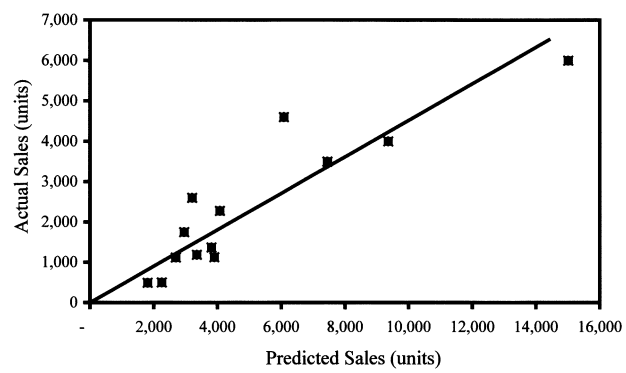
Validation of Sales Estimates

Titan actually introduced all 13 prototypes into the marketplace in 1996, and their sales data for 1996 were subsequently made available to us. The prototypes did not achieve full distribution or awareness in the first year. However, the market performance of the prototypes during 1996 can be compared against the predicted sales for the prototypes for the same year, to validate the predictive power of the source of volume model. The regression equation of the actual 1996 sales against predicted 1996 sales for the prototypes is as follows:

$$\text{Actual Sales} = 0.45 * (\text{Predicted Sales});$$
$$R^2 = 0.78; \qquad \text{t-statistic} = 12.19$$

The actual versus predicted sales are graphed in Figure 2. An intercept, when included, was insignificant. The predictive results provide some validation for the source of volume model used to generate the estimated life-cycle sales volumes. While actual 1996 sales are consistently less than predicted 1996 sales (note that full distribution was not achieved in the first year of rollout, 1996), the correlation between actual and predicted sales for 1996 is 0.9.

Figure 2 Actual Vs. Predicted Sales for Prototypes.



Drivers of Perceived Styling Similarity

The 13 prototypes that were evaluated for the implementation had been designed before the consumer measurement. However, the consumer measurement technique can also guide component standardization decisions *before* line extensions have been designed. For instance, if two models with the same case shape

Table 2 Drivers of Perceived Styling Similarity Between Watch Models

Predictor Variable	Potential Values	Coefficient
Same case shape	Round, Shaped, Oval	1.3856***
Same case finish	Buffed, Matte finish, Dual finish	0.6050**
Same case plating	Gold plating, Ion plating	0.8491**
Same strap material	Brass, Steel, Leather, Solid brass link	0.6300**
Same strap finish	Plain, Buffed, Dual finish	0.4730*
Same dial color	White, Champagne, Black, Gold	0.5893**
Same dial layout	Inserts, Dots, Arabic print, Roman print	0.5768
Same movement functions	Plain (2/3 hands), Day, Day/Date	0.4099
Same brand name	Titan, Other brands	0.3728
Absolute price differential	Absolute price difference in Rupees	−0.0001
Constant		0.9859
Model R^2		0.506
F-ratio		4.309***
Number of observations		53

*** Significant at $p < 0.01$, ** Significant at $p < 0.05$, * Significant at $p < 0.10$.

are perceived to be very similar in styling, this would suggest limited standardization of cases. In the consumer measurement procedure, we obtained measures of perceived styling similarity between each prototype and its baseline models. We regressed these pairwise similarity ratings against the product features to determine the drivers of perceived similarity (see Table 2).

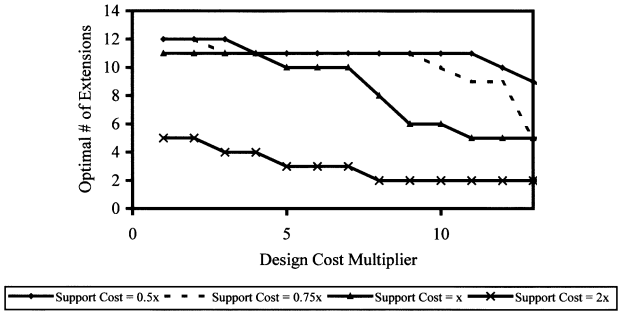
As expected, "below-the-skin" movement functions do not contribute significantly to styling similarity, while the more visible appearance parts (case, dial, strap) do. The case shape has the strongest impact on perceived similarity, suggesting that excessive standardization of cases is not advisable, despite the cost implications of this strategy. Interestingly, the dial color, case finish, case plating, and strap material also significantly impact perceived similarity. This suggests that Titan can create perceived variety cost-effectively by expanding the ranges of these cheaper-to-design attributes. As expected, price and brand names have little impact on styling similarity. Finally, the regression model explains about 50% of the overall variance, suggesting that, while physical component similarity is a strong predictor of styling similarity, the overall "look" of a watch is determined by complex design cues that are difficult to capture on a limited set of physical features. This reinforces the limitations of utility decomposition techniques like conjoint analysis in evaluating consumer response to aesthetic products.

Optimization Results

We implemented our optimization model using marketing and cost inputs for the 13-prototype test problem provided to us by Titan. The optimization model revealed that only 11 of the 13 prototypes should have been introduced to maximize incremental profits. Prototypes 3 and 9 were dropped in the optimal solution. We found that these prototypes had low contribution margins, and both gained over 30% of their life-cycle sales from cannibalization. The optimal profits from using our model, with only 11 line extensions, were 4.89% higher than Titan's incremental profits from introducing all of the 13 line extensions, estimated using our model. Our approach could have increased incremental profits by almost 5%, while introducing fewer line extensions.

Because development costs in India are low, and support costs were likely to be underestimated because we were unable to use ABC for these costs, we examined the sensitivity of the profit-maximizing solution to these costs. We varied development costs from 1× to 15×, and support costs from 0.5× to 2×, of the base level costs provided by Titan. The results, summarized in Figure 3, are consistent with the intuition that optimal variety is decreasing in development and support costs. Interestingly, even if support

Figure 3 **Optimal Number of Line Extensions as a Function of Development and Support Costs.**



costs were half of their base case values, it is still not optimal to introduce all 13 of the line extensions, as Titan in fact did.

Simulation Studies

To test our model's robustness under more general conditions, on larger problems, we constructed a set of test problems based on the data from the empirical application. Each problem included 200 baseline models and 40 potential line extensions, with 5 models in each baseline set. Demand and cost parameters for these problems were drawn from normal distributions, with the mean for each parameter set at the corresponding mean in the empirical application, and the standard deviation calculated based on a coefficient of variation of 10%.

To understand the relative merits of our model under different scenarios in a structured fashion, we introduce the following parameters. The *degree of parts-sharing*, P, is defined as the ratio of the number of line extensions in the master set to the average number of versions of each component used over all the line extensions in this consideration set. A high value for the degree of parts-sharing indicates that relatively few component versions are needed to develop the entire set of line extensions under consideration. For example, in the empirical application, we find that $P = 1.4$, indicating relatively low parts-sharing. We define the *degree of cannibalization* δ^C as the average share points taken by a line extension from each of the firm's own models in its baseline set. The degree of cannibalization in the empirical application was 0.20, indicating a relatively low level of cannibalization.

We first generated a base test problem similar to the empirical application by setting the degree of parts-sharing, $P = 1.4$, resulting in 28 versions of each component to span the master set of 40 line extensions. Each new line extension was randomly assigned a version of each component. We set the degree of cannibalization δ^C at 0.20, the observed value for this parameter in the empirical application.

To understand the relative merits of our model over other approaches, we compared the performance of our model with two functional heuristics, and a more sophisticated cross-functional heuristic that managers might have used in lieu of our optimization model on the base test problem. The heuristics are defined as:

1. A *marketing* heuristic that maximizes the incremental revenues ΔR associated with a set of line extensions, subject to a constraint on the number of models to be introduced.

$$\Delta R = \sum_k X_k \Big\{ p_k^N \big(Q_k^D + Q_k^E\big) + \sum_{\substack{j \in \mathbf{B}_k \\ j \in firm's\ models}} \big(p_k^N - p_j^B\big) Q_{k,j}^C \Big\}.$$

2. An *operations* heuristic that minimizes the incremental costs ΔC associated with a set of line extensions that share components, subject to a constraint on the number of line extensions to be introduced and Constraints (10) through (15).

$$\Delta C = \sum_{k \in N} X_k (d_k + f_k + l_k Q_k^T) + \sum_{c,s} Y_{c,s} d_{c,s} + \sum_{c,s} \big\{ (m_{c,s} + l_{c,s}^1) V_{c,s}^1 + (m_{c,s} + l_{c,s}^2) V_{c,s}^2 \big\}.$$

3. A *cross-functional* heuristic that ranks line extensions in terms of return on investment over the life cycle of each line extension, when picking K out of N new line extensions.

$$ROLI_K = \frac{\big(p_k^N - l_k - \sum_{c,s:k \in S_{c,s}} (m_{c,s} + l_{c,s}^1)\big) Q_k^T}{d_k + f_k + \sum_{c,s:k \in S_{c,s}} d_{c,s}},$$

where $ROLI_K$ denotes the return on life-cycle investment for line extension k.[7]

[7] Using the average of $l_{c,s}^1$ and $l_{c,s}^2$ instead of $l_{c,s}^1$ does not change the nature of our findings.

Figure 4 Percentage Deviation from Optimal Profits for Each Heuristic.

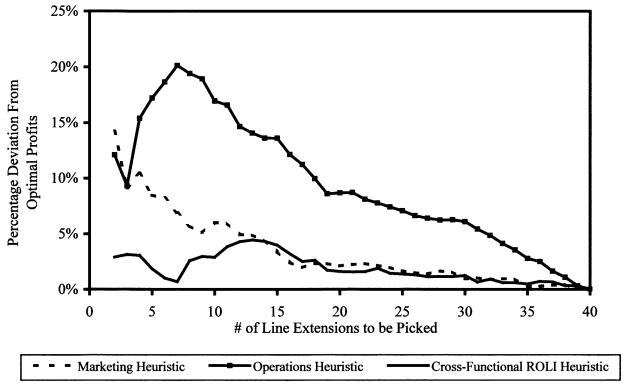


Figure 4 presents the percentage deviation from optimal profits for each heuristic, when compared with that of our optimization model, for the base problem, when the firm's decision was to pick K out of $N = 40$ models, $2 \leq K \leq 40$. $K = 1$ is not relevant, as no parts-sharing is possible here. Of the functional heuristics, the marketing heuristic outperforms the operations heuristic, reflecting the relatively low development and support costs in the application. The cross-functional ROLI heuristic outperforms the functional heuristics, and our model consistently outperforms the ROLI heuristic, for all values of K.

To understand the relative merits of our method over the ROLI heuristic under more general conditions, we created four sets of test problems by keeping the degree of parts-sharing fixed at 1.4 (which was its level in the empirical application), and varying the degree of cannibalization, δ^C, from 0 to 0.3, in increments of 0.1. To interpret the impact of changes in δ^C, we assumed that the total sales volume for each line extension remains constant as δ^C is increased, and that sales volume from demand expansion also remains constant. Therefore, the sales volume from competitive draw reduces as δ^C increases. This allows us to examine the impact of changes in the relative importance of cannibalization and competitive draw as sources of sales volume. We compared the performance of the cross-functional ROLI heuristic with that of our optimization model for each of these test cases, when the firm's decision was to pick K out of $N = 40$ models, $2 \leq K \leq 40$. We found that our model performs better relative to the ROLI heuristic when cannibalization accounts for a larger share of total sales volume relative to competitive draw, consistent with the fact that the ROLI heuristic ignores cannibalization.

Our empirical application involved relatively low parts-sharing among the proposed line extensions ($P = 1.4$). To study the impact of high parts-sharing on the performance of our model relative to the heuristics, we set the degree of parts-sharing, $P = 20$, while keeping the degree of cannibalization δ^C at the baseline level of 0.2. We compared the deviation from optimal profits for the ROLI heuristic when picking K out of $N = 40$ models, where $2 \leq K \leq 40$, under a scenario of high parts-sharing ($P = 20$), with the same measure of performance under a scenario of low parts-sharing ($P = 1.4$). Interestingly, we found that the relative performance of the ROLI heuristic, which ignores parts-sharing, is often better in the case of high parts-sharing. Specifically, when K is large, the deviation from optimal profits for the ROLI heuristic is bigger under a low parts-sharing regime than under a high parts-sharing regime. This seemingly counterintuitive effect can be explained as follows. In a low parts-sharing regime, when picking K out of N models using the ROLI method, if K is large then a large number of different component versions are likely to be used, since the ROLI method ignores parts-sharing. When our model is used in this scenario, it results in significantly fewer component versions being used, thus resulting in significantly higher profits. In a high parts-sharing regime, when K is large, both the ROLI heuristic and our model would likely result in the use of most of the component versions. Thus, the improvement from using our model is small. In contrast, when K is small, in a high parts-sharing regime our model will likely use only one version of each component, while the ROLI method would use more than one version of each component, resulting in lower profits. However when K is small and the degree of parts-sharing is low, both the ROLI heuristic and our model would use several versions of each component, resulting in smaller gains from using our model.

These simulations provide a useful way for modelers to assess the benefit of using our cross-functional model in different problem contexts. First, we find

that our model is most useful when cannibalization strongly dominates draw as a source of volume. Second, we find that if the degree of parts-sharing among proposed line extensions is high, our model is most useful when few line extensions are to be selected from the master set. If the degree of parts-sharing is low, then our model is most beneficial when many line extensions are to be selected.

7. Summary, Limitations, and Future Directions

We proposed a cross-functional approach to evaluating multiple line extensions for assembled products. Our approach has several unique contributions:

1. We propose that consumers evaluate products at the product level, but manufacturers of assembled products create variety at the component level. Using this insight, we develop a modeling approach that incorporates both *revenue interactions* and *cost interactions* among multiple line extensions.

2. We estimate revenue interactions for multiple line extensions at the product level using a source of volume procedure that incorporates cannibalization, competitive draw and demand expansion, and cost interactions at the component level via an enhanced ABC procedure for life-cycle new product costs.

3. We develop an optimization model to select a profit-maximizing set of line extensions that incorporates both revenue and cost interactions. We present a real-life implementation, and demonstrate our model's economic benefit. Via simulation analyses, we identify problem contexts where our cross-functional approach is most beneficial, relative to heuristics.

In addressing a complex problem, we made several assumptions. We assume that management is able to correctly identify a baseline set for each line extension. While managers in our application were comfortable doing this, a formal categorization task may be useful to verify managerial assessments. We did not directly estimate pairwise cannibalization among prototypes, and our estimate of demand expansion ignores cross-selling, where consumers might purchase two different models. We also ignored uncertainty in parametric estimates, time-to-market, and competitive reactions that are other key determinants of optimal product line variety.

As in standard ABC systems, we assume that the usage of support resources is linear in the cost drivers. However, discussions with managers suggest that costs may in fact increase steeply with variety. Estimating this nonlinearity in costs is a fruitful area for future research.

We address only the question of *what* product line extensions to introduce, not *how* to produce them. An interesting extension would be to segment manufacturing capacity into buckets with differing production rates and flexibility levels, include these as capacity constraints, and optimally allocate the line extensions to the available capacity types. Finally, high-variety manufacturers often make product line *pruning* decisions based on sales performance. However, some low-volume products may bring in sales primarily from competitive draw and demand expansion, or may be low-cost products. A model that evaluates the impact of pruning on product-line profitability would be useful in practice.

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Appendix

Let $\alpha_{c,s} \geq 0$ and $\beta_{c,s} \geq 0$ denote the Lagrangean multipliers for Constraints (10) and (11) of the cross-functional model. For given $\alpha_{c,s}$ and $\beta_{c,s}$, the Lagrangean subproblem is:

$$\begin{aligned}\text{Max} \quad & \sum_{k\in N} X_k \Bigg\{ \Delta R_k + \sum_{\substack{j\in \mathbf{B}_k \\ j\in firm's\ models}} c_j Q^C_{k,j} - l_k Q^T_k - d_k - f_k \\ & \qquad - \sum_{c,s:k\in S_{c,s}} \alpha_{c,s} - Q^T_k \cdot \sum_{c,s:k\in \mathbf{S}_{c,s}} \beta_{c,s} \Bigg\} \\ & - \sum_{c,s} Y_{c,s}\left(d_{c,s} - \alpha_{c,s}\right) \\ & - \sum_{c,s} \Big\{ \left(m_{c,s} + l^1_{c,s} - \beta_{c,s}\right) V^1_{c,s} + \left(m_{c,s} + l^2_{c,s} - \beta_{c,s}\right) V^2_{c,s} \Big\},\end{aligned}$$

subject to (12), (13), (14), and (15). This problem can be solved by inspection. For all k

$$X_k = 1$$

if

$$\Delta R_k + \sum_{\substack{j\in \mathbf{B}_k \\ j\in firm's\ models}} c_j Q^C_{k,j} - l_k Q^T_k - d_k - f_k - \sum_{c,s:k\in \mathbf{S}_{c,s}} \alpha_{c,s} - Q^T_k \cdot \sum_{c,s:k\in \mathbf{S}_{c,s}} \beta_{c,s} > 0,$$

or else, $X_k = 0$. For all c, s: $Y_{c,s} = 1$ if $(d_{c,s} - \alpha_{c,s}) > 0$. Or else, $Y_{c,s} = 0$. Also, $V^1_{c,s} = V^2_{c,s} = W_{c,s} = 0$. To obtain a feasible solution to the original model from the solution to the Lagrangean subproblem: For each c, s: if $\sum_{k \in \mathbf{S}_{c,s}} X_k > 0$, then set $Y_{c,s} = 1$. Or else, set $Y_{c,s} = 0$. For each c, s: If $Y_{c,s} = 0$, then $V^1_{c,s} = 0$, $V^2_{c,s} = 0$, $W_{c,s} = 0$. If $Y_{c,s} = 1$, then $V^1_{c,s} = \min\{\sum_{k \in S_{c,s}} X_k Q^T_k, E_{c,s}\}$. If $V^1_{c,s} = E_{c,s}$, then $V^2_{c,s} = \sum_{k \in S_{c,s}} X_k Q^T_k - E_{c,s}$; or else, $V^2_{c,s} = 0$. A standard subgradient procedure is used to update the Lagrangean multipliers, $\alpha_{c,s} \geq 0$ and $\beta_{c,s} \geq 0$. The Lagrangean heuristic provided the optimal solution to the Titan application.

References

Cohen, M.A., J. Eliashberg, T.H. Ho. 1997. An anatomy of a decision-support system for developing and launching line extensions. *J. Marketing Res.* **34** 117–129.

Cooper, R., R.S. Kaplan. 1988. Measure costs right: Make the right decisions. *Harvard Bus. Rev.* (September–October) 96–103.

Dahan, E., V.S. Srinivasan. 1998. The predictive power of Internet-based product concept testing using visual depiction and animation. Working paper, MIT Sloan School, Cambridge, MA.

Dobson, G., S. Kalish. 1988. Positioning and pricing a product line. *Marketing Sci.* **7** 107–125.

———, ———. 1993. Heuristics for pricing and positioning a product-line using conjoint and cost data. *Management Sci.* **39**(2) 160–175.

———, C.A. Yano. 1995. Product line and technology selection with shared manufacturing and engineering design resources. Working paper, Operations Management, University of Rochester, Rochester, NY.

Fisher, M.L. 1985. An applications-oriented guide to Lagrangian relaxation. *Interfaces* **15**(2) 10–21.

———, K. Ramdas, K.T. Ulrich. 1999. Component sharing in the management of product variety: A study of automotive braking systems. *Management Sci.* **45**(5) 297–315.

Foster, G., M. Gupta. 1990. Activity accounting: An electronics industry implementation. R.S. Kaplan, ed. *Measures for Manufacturing Excellence*. 225–268.

Green, P.E., A.M. Krieger. 1985. Models and heuristics for product line selection. *Marketing Sci.* **4**(Winter) 1–19.

Gupta, S., V. Krishnan. 1999. A product family-based approach for integrated component and supplier selection. *Production Oper. Management* **8**(2) 163–182.

Hertenstein, J.H., M.B. Platt. 1998. Why product development teams need management accountants. *Management Accounting* **79**(10) 50–55.

Kahn, B. 1998. Dynamic relationships with customers: High-variety strategies. *J. Acad. Marketing Sci.* **26**(1) 45–53.

Krishnan, V., R. Singh, D. Tirupati. 1999. A model-based approach for planning and developing a family of technology-based products. *Manufacturing and Services Oper. Management* **1**(2) 132–156.

Lancaster, K.J. 1966. A new approach to consumer theory. *J. Political Econom.* **74** 132–157.

———. 1990. The economics of product variety: A survey. *Marketing Sci.* **9** 189–206.

MacDuffie, J.P., K. Sethuraman, M. L. Fisher. 1996. Product variety and manufacturing performance: Evidence from the international automotive assembly plant study. *Management Sci.* **42**(3) 350–369.

McBride, R.D., F.S. Zufryden. 1988. An integer programming approach to the optimal product line selection problem. *Marketing Sci.* **7** 126–140.

Nair, S.K., L.S. Thakur, K.W. Wen. 1995. Near optimal solutions for product line design and selection: Beam selection heuristics. *Management Sci.* **41**(5) 767–785.

Raman, N., D. Chhajed. 1995. Simultaneous determination of product attributes and prices, and production processes in product-line design. *J. Oper. Management* **12** 187–204.

Ramdas, K. 1995. Using parts sharing to manage product variety: A study in the automobile industry. Unpublished Ph.D. thesis, The Wharton School, University of Pennsylvania, Philadelphia, PA.

Rutenberg, D.P. 1969. Design commonality to reduce multi-item inventory: Optimal depth of a product line. *Management Sci.* **15** 491–509.

Sawhney, M. 1998. Leveraged high-variety strategies: From portfolio thinking to platform thinking. *J. Acad. Marketing Sci.* **26**(1) 54–61.

Schmalensee, R., J.F. Thisse. 1986. Perceptual maps and the optimal location of new products: An integrative essay. *Internat. J. Res. Marketing* **5** 225–249.

Silk, A.J., G.L. Urban. 1978. Pre-test-market evaluation of new packaged goods: A model and measurement methodology. *J. Marketing Res.* **15** 171–191.

Srinivasan, V., W.S. Lovejoy, D. Beach. 1997. Integrated product design for marketability and manufacturing. *J. Marketing Res.* **34** (February) 154–163.

Ulrich, K. 1995. The role of product architecture in the manufacturing firm. *Res. Policy*. **24** 419–440.

———, D.J. Ellison. 1999. Customer requirements and the design-select decision. *Management Sci.* **45**(5) 641–658.

Urban, G.L. 1993. Pretest market forecasting. *Handbooks in Operations Research and Management Science, Vol. 5: Marketing*. North-Holland, Amsterdam, The Netherlands. 315–347.

———, P. Johnson, J.R. Hauser. 1984. Testing competitive market structures. *Marketing Sci.* **3** (Spring) 83–112.

Yano, C.A., G. Dobson. 1998. Profit optimizing product line design, selection and pricing with manufacturing cost consideration. T.H. Ho, C.S. Tang, eds. *Product Variety Management: Research Advances*. Kluwer Academic Publishers, Amsterdam, The Netherlands.

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